Search Engines

Information Retrieval in Practice

Social Search

- Social search
  - *Communities* of users *actively participating* in the search process
  - Goes beyond classical search tasks
- Key differences
  - Users interact with the system
  - Users interact with other users either implicitly or explicitly

Web 2.0

- Social search includes, but is not limited to, the so-called social media sites
  - Collectively referred to as “Web 2.0” as opposed to the classical notion of the Web (“Web 1.0”)
- Social media sites
  - User generated content
  - Users can tag their own and other’s content
  - Users can share favorites, tags, etc., with others
- Examples:
  - Digg, Twitter, Flickr, YouTube, Del.icio.us, CiteULike, MySpace, Facebook, and LinkedIn

Social Search Topics

- User tags
- Searching within communities
- Adaptive filtering
- Recommender systems
- Peer-to-peer and metasearch

User Tags and Manual Indexing

- Then: Library card catalogs
  - Indexing terms chosen with search in mind
  - Experts generate indexing terms
  - Terms are very high quality
  - Terms chosen from controlled vocabulary
- Now: Social media tagging
  - Tags not always chosen with search in mind
  - Users generate tags
  - Tags can be noisy or even incorrect
  - Tags chosen from *folksonomies*

Types of User Tags

- Content-based
  - car, woman, sky
- Context-based
  - new york city, empire state building
- Attribute
  - nikon (type of camera), black and white (type of movie), homepage (type of web page)
- Subjective
  - pretty, amazing, awesome
- Organizational
  - to do, my pictures, readme

Searching Tags

- Searching user tags is challenging
  - Most items have only a few tags
  - Tags are very short
- Boolean, probabilistic, vector space, and language modeling will fail if use naïvely
- Must overcome the ***vocabulary mismatch problem*** between the query and tags

Tag Expansion

- Can overcome vocabulary mismatch problem by expanding tag representation with external knowledge
- Possible external sources
  - Thesaurus
  - Web search results
  - Query logs
- After tags have been expanded, can use standard retrieval models

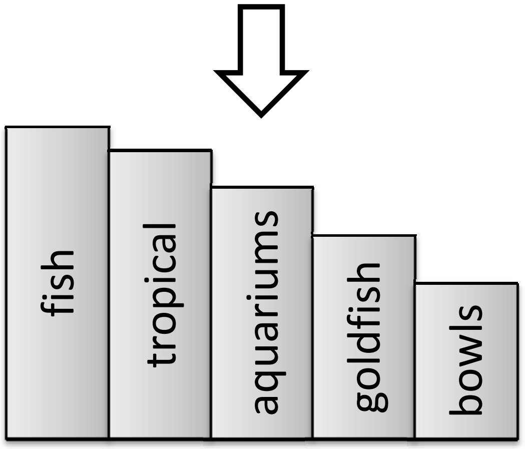
Tag Expansion Using Search Results

Age of Aquariums - **Tropical Fish**
Huge educational aquarium site for **tropical fish** hobbyists, promoting responsible **fish** keeping internationally since 1997.

The Krib (Aquaria and **Tropical Fish**)
This site contains information about **tropical fish** aquariums, including archived usenet postings and e-mail discussions, along with new ...

...

Keeping **Tropical Fish** and Goldfish in Aquariums, **Fish** Bowls, and ...
Keeping **Tropical Fish** and Goldfish in Aquariums, **Fish** Bowls, and Ponds at AquariumFish.net.



P(w | “tropical fish”)

Searching Tags

- Even with tag expansion, searching tags is challenging
- Tags are inherently noisy and incorrect
- Many items may not even be tagged!
- Typically easier to find popular items with many tags than less popular items with few/no tags

Inferring Missing Tags

- How can we automatically tag items with few or no tags?
- Uses of inferred tags
  - Improved tag search
  - Automatic tag suggestion

Methods for Inferring Tags

- TF.IDF
  - Suggest tags that have a high TF.IDF weight in the item
  - Only works for textual items
- Classification
  - Train binary classifier for each tag
  - Performs well for popular tags, but not as well for rare tags
- Maximal marginal relevance
  - Finds tags that are relevant to the item and novel with respect to existing tags
  - $MMR(t;T_i) = \left(\lambda Sim_{item}(t,i) - (1-\lambda)\max_{t \in T_i} Sim_{tag}(t_i,t)\right)$

Browsing and Tag Clouds

- Search is useful for finding items of interest
- Browsing is more useful for exploring collections of tagged items
- Various ways to visualize collections of tags
  - Tag lists
  - Tag clouds
  - Alphabetical order
  - Grouped by category
  - Formatted/sorted according to popularity

Example Tag Cloud

animals architecture art australia autumn baby band barcelona beach berlin
birthday black blackandwhite blue california cameraphone canada canon
car cat chicago china christmas church city clouds color concert day dog
england europe family festival film florida flower flowers food
france friends fun garden germany girl graffiti green halloween hawaii
holiday home house india ireland italy japan july kids lake landscape light live
london macro me mexico music nature new newyork night
nikon nyc ocean paris park party people portrait red river rock
sanfrancisco scotland sea seattle show sky snow spain spring street
summer sunset taiwan texas thailand tokyo toronto travel
tree trees trip uk usa vacation washington water wedding

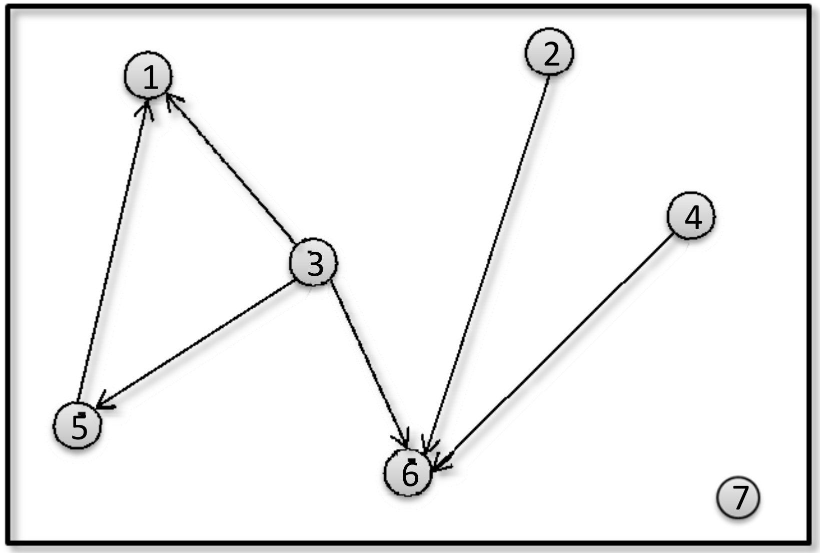
Searching with Communities

- What is an online community?
  - Groups of entities that interact in an online environment and share common goals, traits, or interests
- Examples
  - Baseball fan community
  - Digital photography community
- Not all communities are made up of humans!
  - Web communities are collections of web pages that are all about a common topic

Finding Communities

- What are the characteristics of a community?
  - Entities within a community are similar to each other
  - Members of a community are likely to interact more with other members of the community than those outside of the community
- Can represent interactions between a set of entities as a graph
  - Vertices are entities
  - Edges (directed or undirected) indicate interactions between the entities

Graph Representation



$$\begin{array}{lccccccc}
\underline{\text{Node:}} & 1 & 2 & 3 & 4 & 5 & 6 & 7 \\
\underline{\text{Vector:}} &
\begin{bmatrix}0\\0\\0\\0\\0\\0\\0\end{bmatrix} &
\begin{bmatrix}0\\0\\0\\0\\0\\1\\0\end{bmatrix} &
\begin{bmatrix}1\\0\\0\\0\\1\\1\\0\end{bmatrix} &
\begin{bmatrix}0\\0\\0\\0\\0\\1\\0\end{bmatrix} &
\begin{bmatrix}1\\0\\0\\0\\0\\0\\0\end{bmatrix} &
\begin{bmatrix}0\\0\\0\\0\\0\\0\\0\end{bmatrix} &
\begin{bmatrix}0\\0\\0\\0\\0\\0\\0\end{bmatrix}
\end{array}$$

HITS

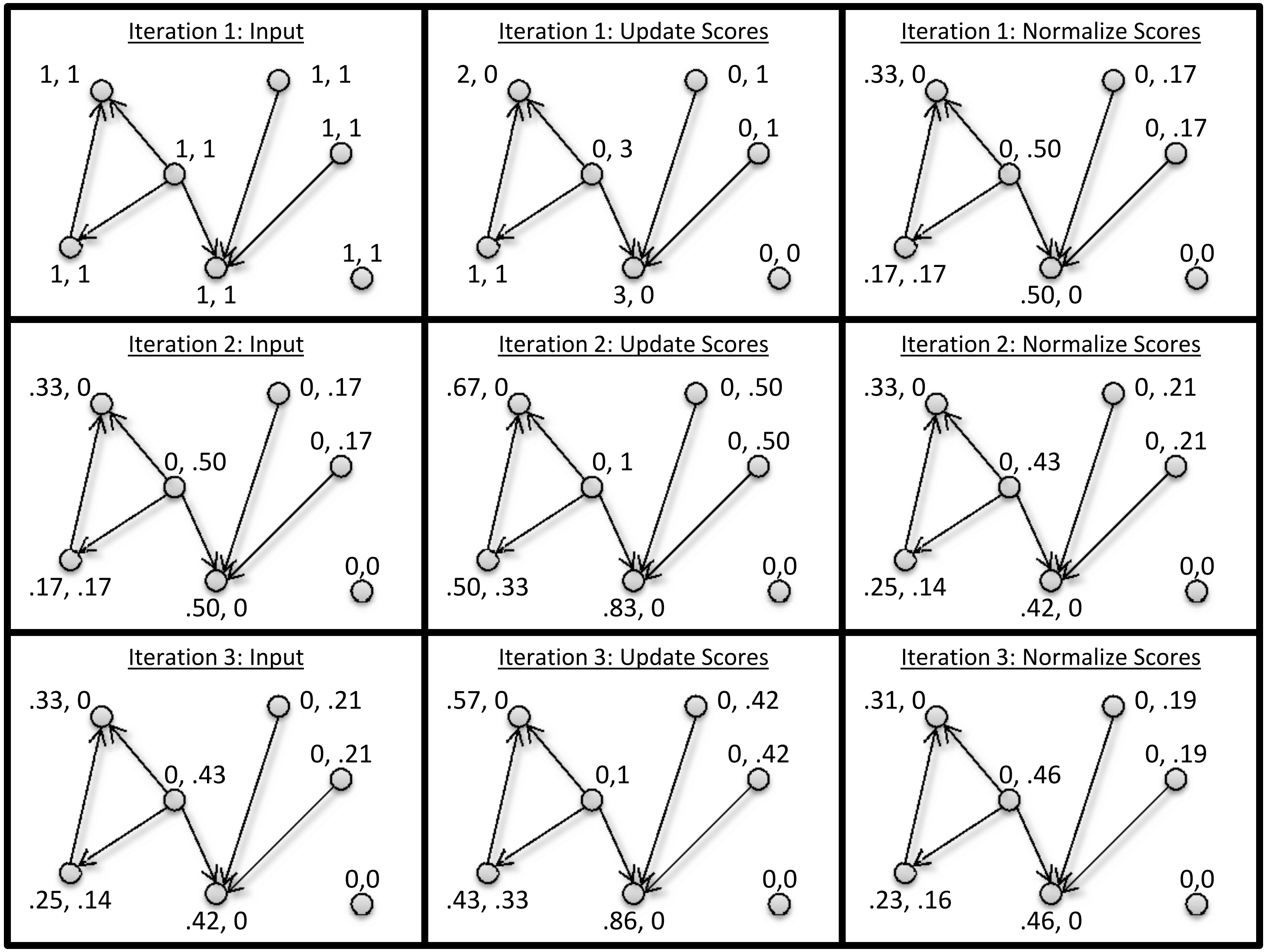
- Hyperlink-induced Topic Search (HITS) algorithm can be used to find communities
  - Link analysis algorithm, like PageRank
  - Each entity has a hub and authority score
- Based on a circular set of assumptions
  - Good hubs point to good authorities
  - Good authorities are pointed to by good hubs
- Iterative algorithm:

$$\begin{aligned} A(p) &= \sum_{q \rightarrow p} H(q) \\ H(p) &= \sum_{p \rightarrow q} A(q) \end{aligned}$$

Algorithm 1 HITS

```
1: procedure HITS($G = (V, E), K$)
2:     $A_0(p) \leftarrow 1 \ \forall p \in V$
3:     $H_0(p) \leftarrow 1 \ \forall p \in V$
4:     for $i = 1$ to $K$ do
5:         $A_i(p) \leftarrow 0 \ \forall p \in V$
6:         $H_i(p) \leftarrow 0 \ \forall p \in V$
7:         $Z_A \leftarrow 0$
8:         $Z_H \leftarrow 0$
9:         for $p \in V$ do
10:            for $q \in V$ do
11:                if $(p, q) \in E$ then
12:                    $H_i(p) \leftarrow H_i(p) + A_{i-1}(q)$
13:                    $Z_H \leftarrow Z_H + A_{i-1}(q)$
14:                end if
15:                if $(q, p) \in E$ then
16:                    $A_i(p) \leftarrow A_i(p) + H_{i-1}(q)$
17:                    $Z_A \leftarrow Z_A + H_{i-1}(q)$
18:                end if
19:            end for
20:        end for
21:        for $p \in V$ do
22:            $A_i(p) \leftarrow \frac{A_i(p)}{Z_A}$
23:            $H_i(p) \leftarrow \frac{H_i(p)}{Z_H}$
24:        end for
25:    end for
26:    return $A_K, H_K$
27: end procedure
```

HITS Example



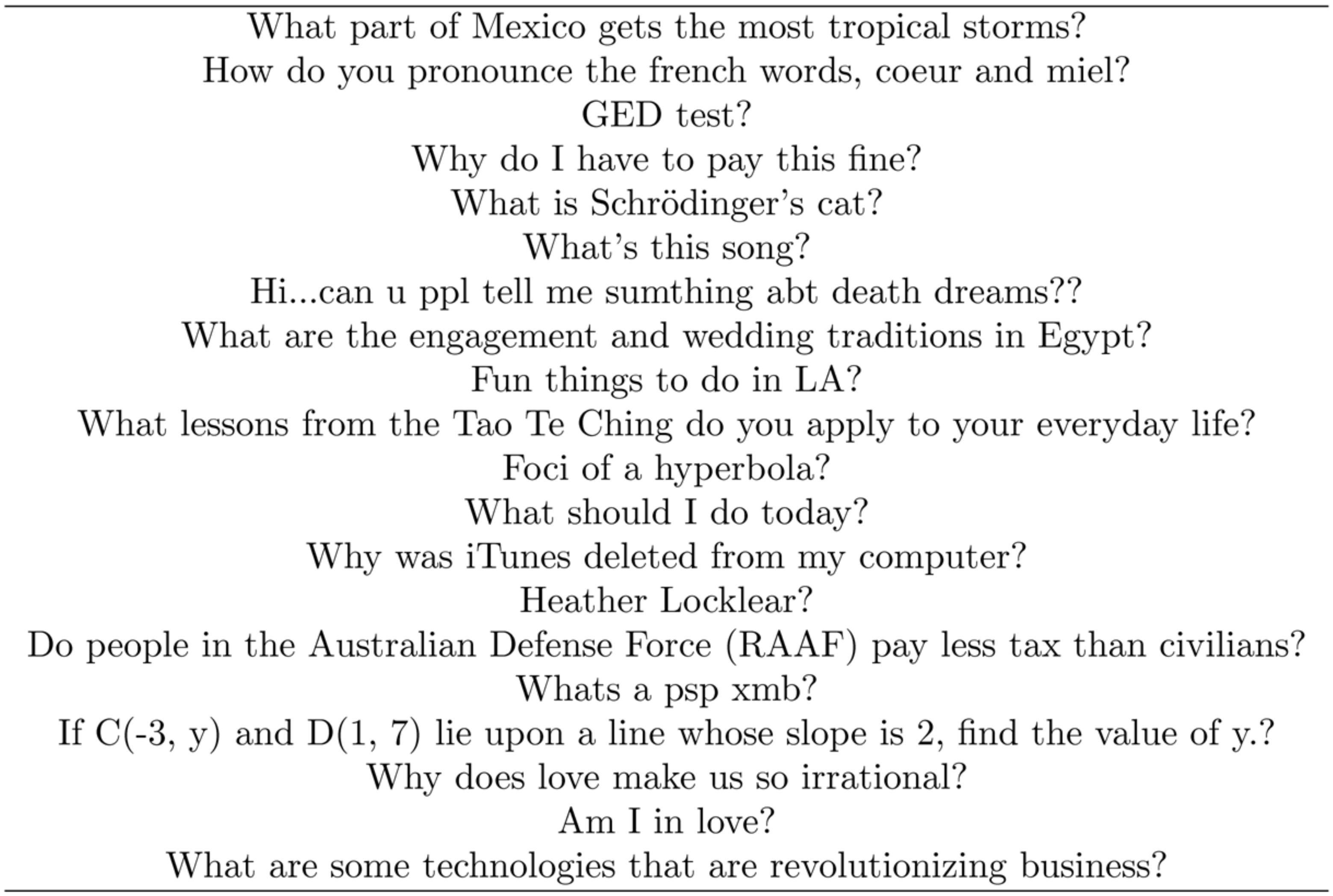
Finding Communities

- HITS
  - Can apply HITS to entity interaction graph to find communities
  - Entities with large authority scores are the “core” or “authoritative” members of the community
- Clustering
  - Apply agglomerative or *K*-means clustering to entity graph
  - How to choose K?
- Evaluating community finding algorithms is hard
- Can use communities in various ways to improve search, browsing, expert finding, recommendation, etc.

Community Based Question Answering

- Some complex information needs can’t be answered by traditional search engines
  - Information from multiple sources
  - Human expertise
- Community based question answering tries to overcome these limitations
  - Searcher enters question
  - Community members answer question

Example Questions



What part of Mexico gets the most tropical storms?
How do you pronounce the french words, coeur and miel?
GED test?
Why do I have to pay this fine?
What is Schrödinger's cat?
What's this song?
Hi...can u ppl tell me sumthing abt death dreams??
What are the engagement and wedding traditions in Egypt?
Fun things to do in LA?
What lessons from the Tao Te Ching do you apply to your everyday life?
Foci of a hyperbola?
What should I do today?
Why was iTunes deleted from my computer?
Heather Locklear?
Do people in the Australian Defense Force (RAAF) pay less tax than civilians?
Whats a psp xmb?
If C(-3, y) and D(1, 7) lie upon a line whose slope is 2, find the value of y.?
Why does love make us so irrational?
Am I in love?
What are some technologies that are revolutionizing business?

Community Based Question Answering

- Pros
  - Can find answers to complex/obscure questions
  - Answers are from humans, not algorithms
  - Can search archive of previous questions/answers
- Cons
  - Often takes time to get a response
  - Some questions never get answered
  - Answers may be wrong

Question Answering Models

- How can we effectively search an archive of question/answer pairs?
- Can be treated as a translation problem
  - Translate a question into a related question
  - Translate a question into an answer
- Translation-based language model:

$$P(Q|A) = \prod_{w \in Q} \sum_{t \in \mathcal{V}} P(w|t)P(t|A)$$

- Enhanced translation model:

$$P(Q|A) = \prod_{w \in Q} \frac{(1-\beta) f_{w,A} + \beta \sum_{t \in \mathcal{V}} P(w|t) f_{t,A} + \mu \frac{c_w}{|C|}}{|A| + \mu}$$

Computing Translation Probabilities

- Translation probabilities are learned from a *parallel corpus*
- Most often used for learning inter-language probabilities
- Can be used for intra-language probabilities
  - Treat question / answer pairs are parallel corpus
- Various tools exist for computing translation probabilities from a parallel corpus

Example Question/Answer Translations

everest	xp	search
everest	xp	search
mountain	window	google
tallest	install	information
29,035	drive	internet
highest	computer	website
mt	version	web
ft	click	list
measure	pc	free
feet	program	info
mount	microsoft	page

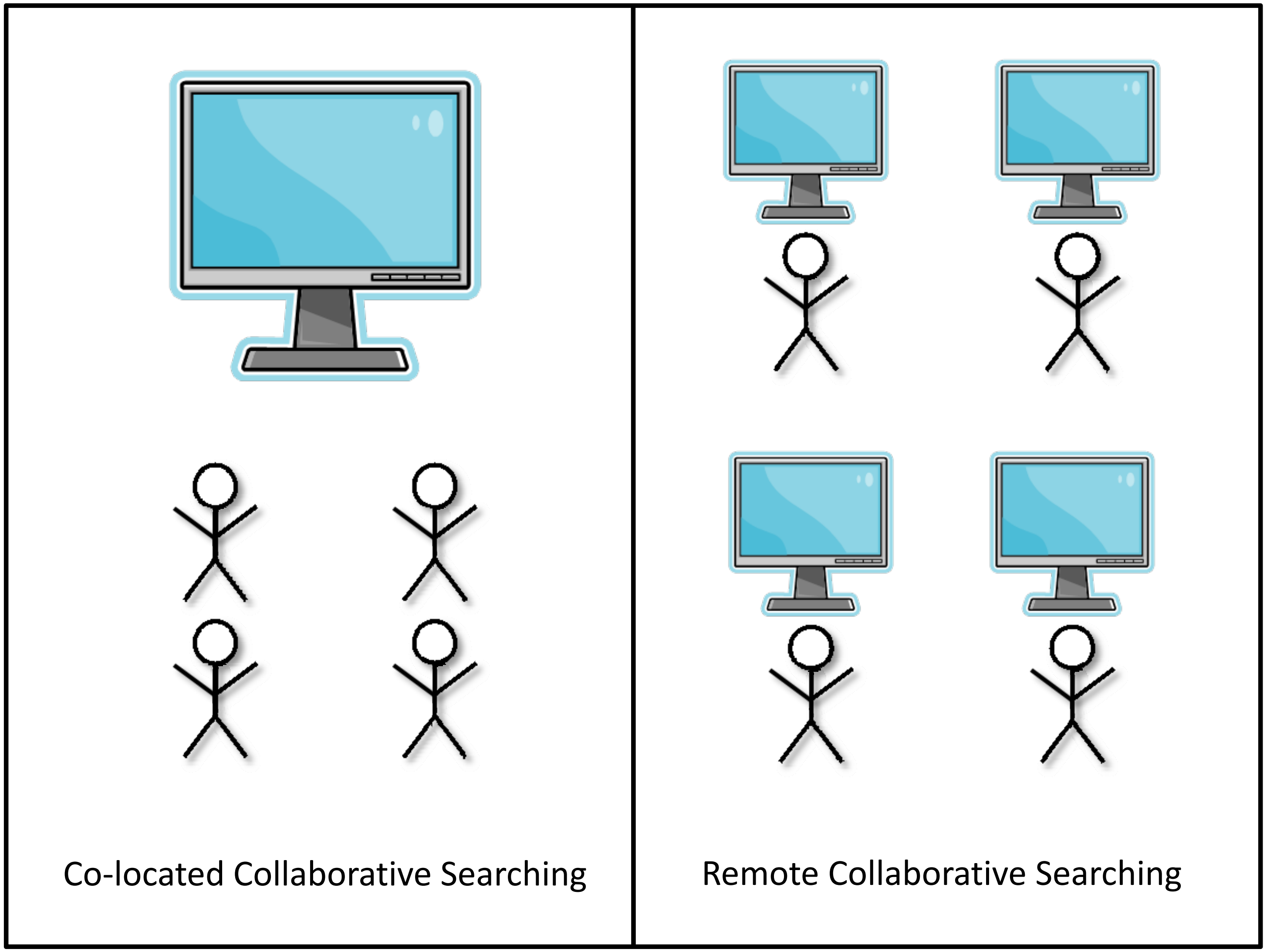
Collaborative Searching

- Traditional search assumes single searcher
- Collaborative search involves a group of users, with a common goal, searching together in a collaborative setting
- Example scenarios
  - Students doing research for a history report
  - Family members searching for information on how to care for an aging relative
  - Team member working to gather information and requirements for an industrial project

Collaborative Search

- Two types of collaborative search settings depending on where participants are physically located
- Co-located
  - Participants in same location
  - CoSearch system
- Remove collaborative
  - Participants in different locations
  - SearchTogether system

Collaborative Search Scenarios


Co-located Collaborative Searching
Remote Collaborative Searching

Collaborative Search

- Challenges
  - How do users interact with system?
  - How do users interact with each other?
  - How is data shared?
  - What data persists across sessions?
- Very few commercial collaborative search systems
- Likely to see more of this type of system in the future

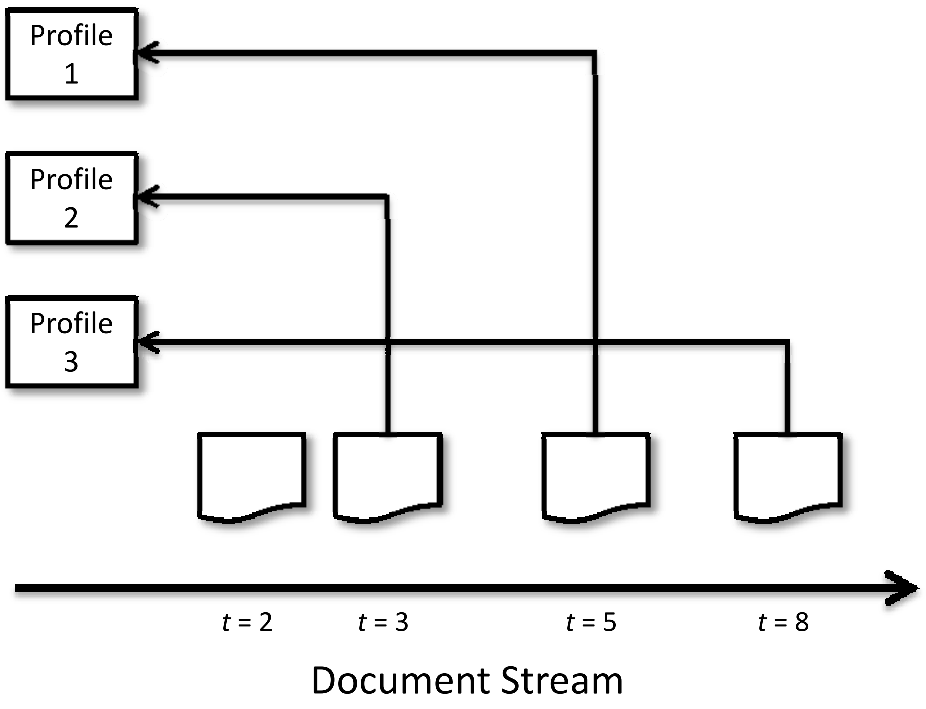
Document Filtering

- Ad hoc retrieval
  - Document collections and information needs change with time
  - Results returned when query is entered
- Document filtering
  - Document collections change with time, but information needs are static (long-term)
  - Long term information needs represented as a *profile*
  - Documents entering system that match the profile are delivered to the user via a *push* mechanism

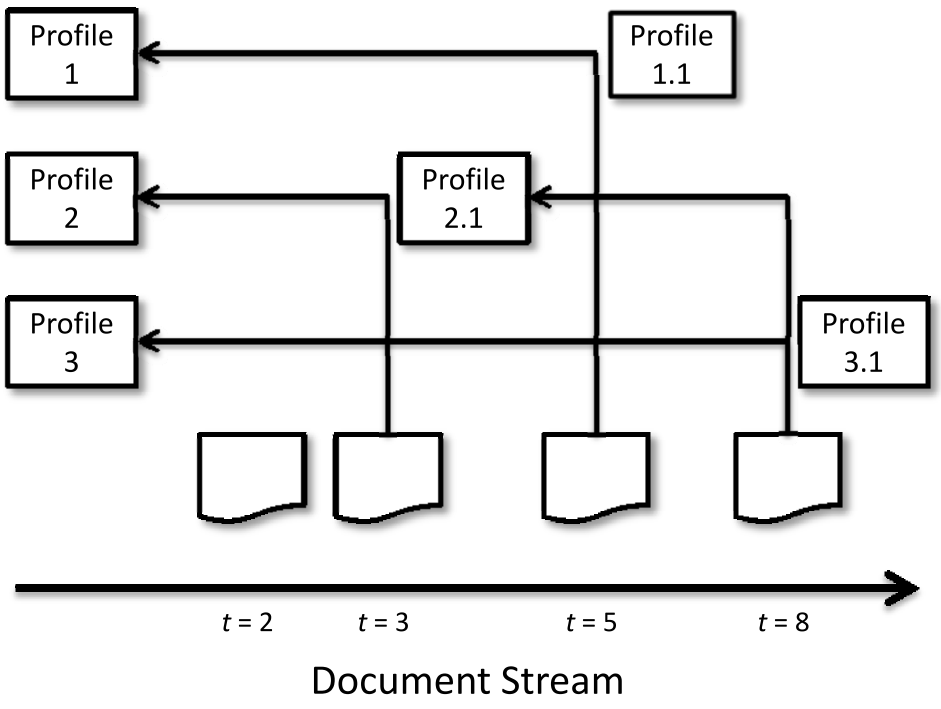
Profiles

- Represents long term information needs
- Can be represented in different ways
  - Boolean or keyword query
  - Sets of relevant and non-relevant documents
  - Relational constraints
    - “published before 1990”
    - “price in the $10-$25 range”
- Actual representation usually depends on underlying filtering model
- Can be static (static filtering) or updated over time (adaptive filtering)

Document Filtering Scenarios



Static Filtering



Adaptive Filtering

Static Filtering

- Given a fixed profile, how can we determine if an incoming document should be delivered?
- Treat as information retrieval problem
  - Boolean
  - Vector space
  - Language modeling
- Treat as supervised learning problem
  - Naïve Bayes
  - Support vector machines

Static Filtering with Language Models

- Assume profile consists of *K* relevant documents (T_i), each with weight α_i
- Probability of a word given the profile is:

$$P(w|P) = \frac{(1-\lambda)}{\sum_{i=1}^{K} \alpha_i} \sum_{i=1}^{K} \alpha_i \frac{f_{w,T_i}}{|T_i|} + \lambda \frac{c_w}{|C|}$$

- KL divergence between profile and document model is used as score:

$$-KL(P||D) = \sum_{w \in V} P(w|P) \log P(w|D) - \sum_{w \in V} P(w|P) \log P(w|P)$$

- If $-KL(P||D) \geq \theta$, then deliver *D* to *P*
  - Threshold (θ) can be optimized for some metric

Adaptive Filtering

- In adaptive filtering, profiles are dynamic
- How can profiles change?
  - User can explicitly update the profile
  - User can provide (relevance) feedback about the documents delivered to the profile
  - Implicit user behavior can be captured and used to update the profile

Adaptive Filtering Models

- Rocchio
  - Profiles treated as vectors

$$P' = \alpha.P + \beta.\frac{1}{|Rel|}\sum_{D_i \in Rel} D_i - \gamma.\frac{1}{|Nonrel|}\sum_{D_i \in Nonrel} D_i$$

- Relevance-based language models
  - Profiles treated as language models

$$\begin{aligned} P(w|P) &= \frac{1}{|Rel|}\sum_{D_i \in Rel}\sum_{D \in \mathcal{C}} P(w|D)P(D_i|D) \\ &\approx \frac{1}{|Rel|}\sum_{D_i \in Rel} P(w|D_i) \end{aligned}$$

Summary of Filtering Models

Model	*Profile Representation*	*Profile Updating*
Boolean	Boolean Expression	N/A
Vector Space	Vector	Rocchio
Language Modeling	Probability Distribution	Relevance Modeling
Classification	Model Parameters	Online Learning

Fast Filtering with Millions of Profiles

- Real filtering systems
  - May have thousands or even millions of profiles
  - Many new documents will enter the system daily
- How to efficiently filter in such a system?
  - Most profiles are represented as text or a set of features
  - Build an inverted index for the profiles
  - Distill incoming documents as “queries” and run against index

Evaluation of Filtering Systems

- Definition of “good” depends on the purpose of the underlying filtering system

	Relevant	Non-Relevant
Retrieved	TP	FP
Not retrieved	FN	TN

- Generic filtering evaluation measure:

$$U = \alpha \cdot TP + \beta \cdot TN + \delta \cdot FP + \gamma \cdot FN$$

- α = 2, β = 0, δ = -1, and γ = 0 is widely used

Collaborative Filtering

- In static and adaptive filtering, users and their profiles are assumed to be independent of each other
- Similar users are likely to have similar preferences
- *Collaborative filtering* exploits relationships between users to improve how items (documents) are matched to users (profiles)

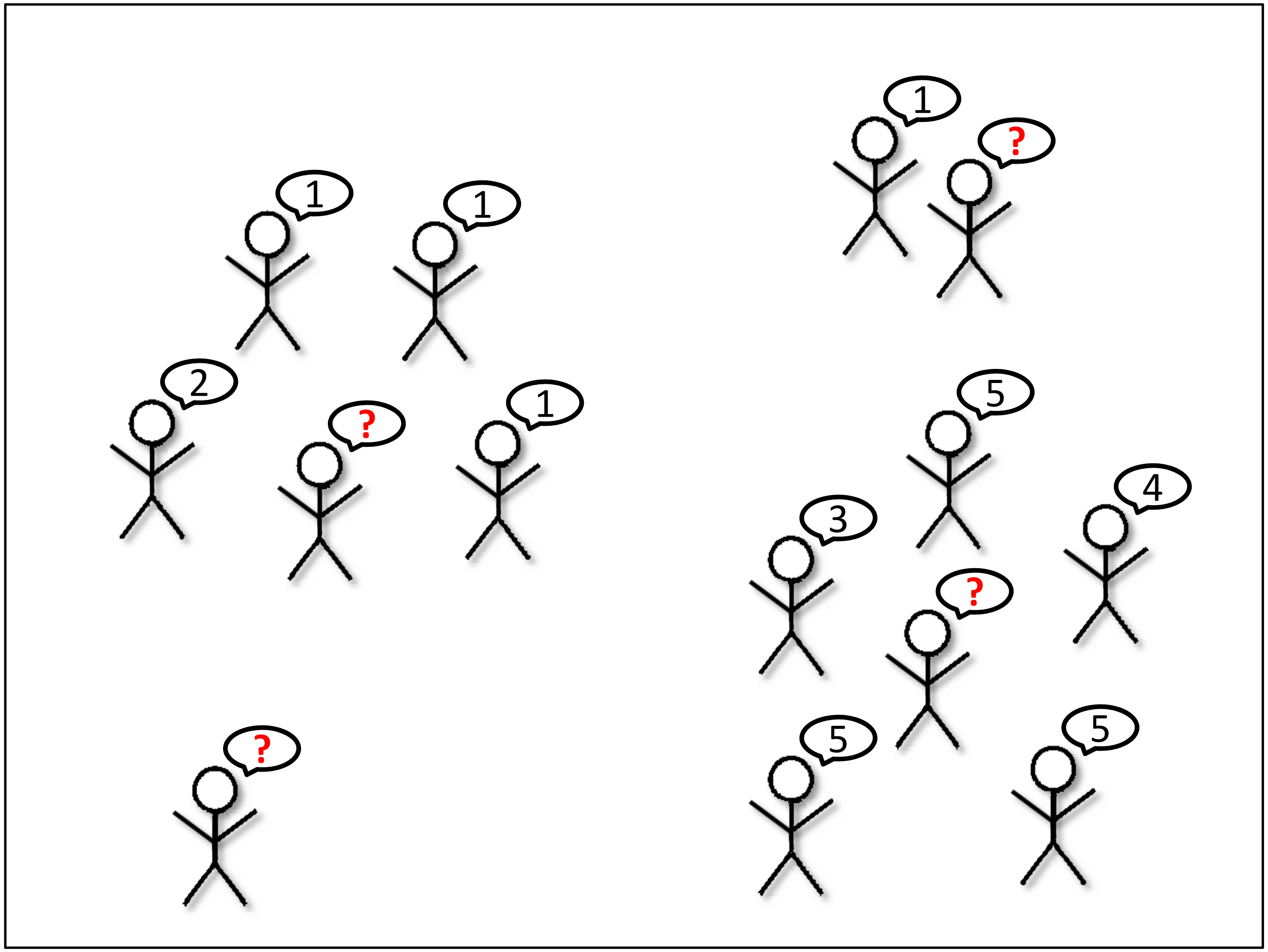
Recommender Systems

- Recommender systems recommend items that a user may be interested in
- Examples
  - Amazon.com
  - NetFlix
- Recommender systems use collaborative filtering to recommend items to users

Recommender System Algorithms

- Input
  - (user, item, rating) tuples for items that the user has explicitly rated
  - Typically represented as a user-item matrix
- Output
  - (user, item, rating) tuples for items that the user has not rated
  - Can be thought of as filling in the missing entries of the user-item matrix
- Most algorithms infer missing ratings based on the ratings of similar users

Recommender Systems



Rating using User Clusters

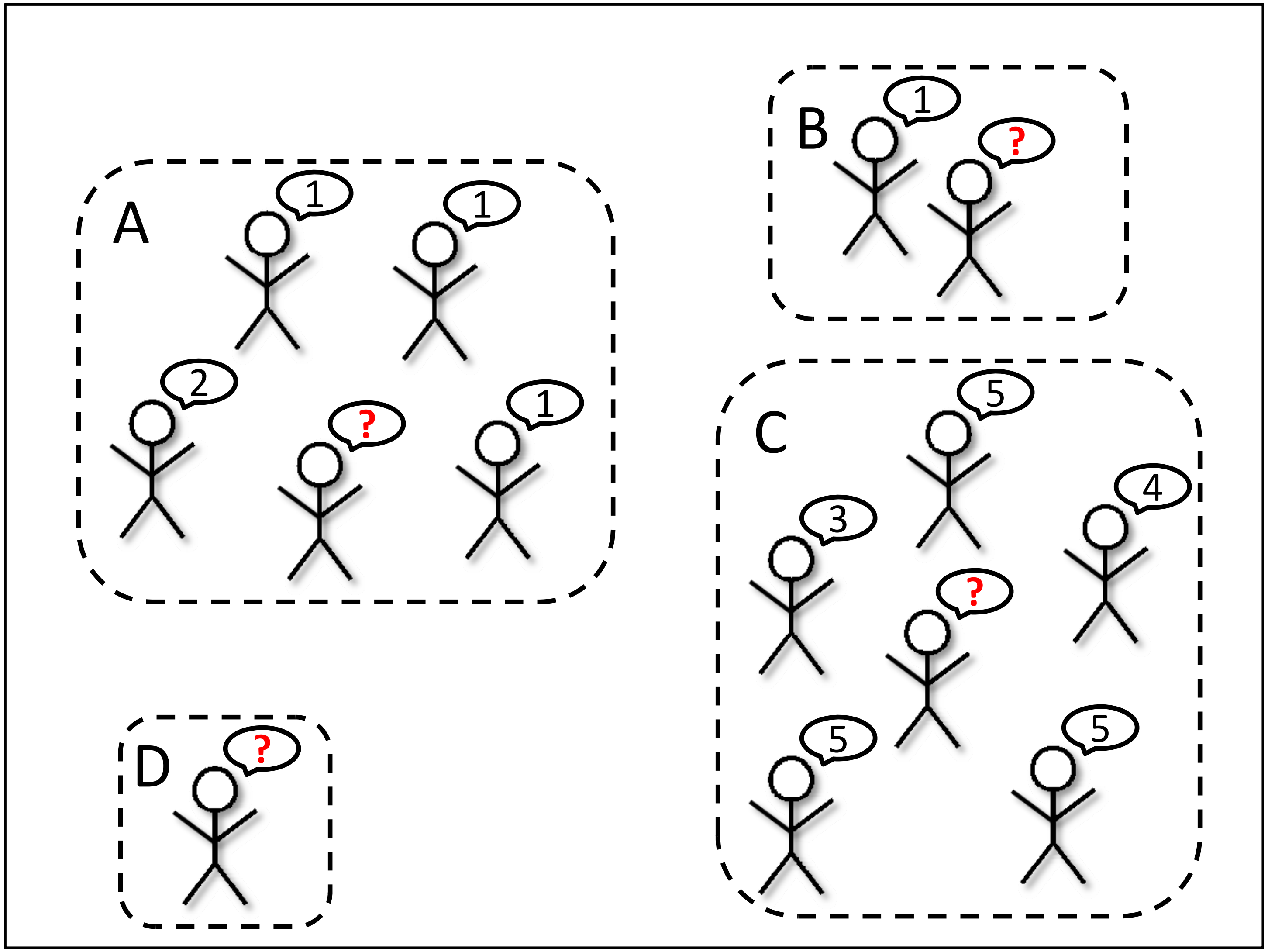
- Clustering can be used to find groups of similar users
- Measure user/user similarity using rating correlation:

$$\frac{\sum_{i \in I_u \cap I_{u'}} (r_u(i) - \hat{r}_u) \cdot (r_{u'}(i) - \hat{r}_{u'})}{\sqrt{\sum_{i \in I_u \cap I_{u'}} (r_u(i) - \hat{r}_u)^2 \sum_{i \in I_u \cap I_{u'}} (r_{u'}(i) - \hat{r}_{u'})^2}}$$

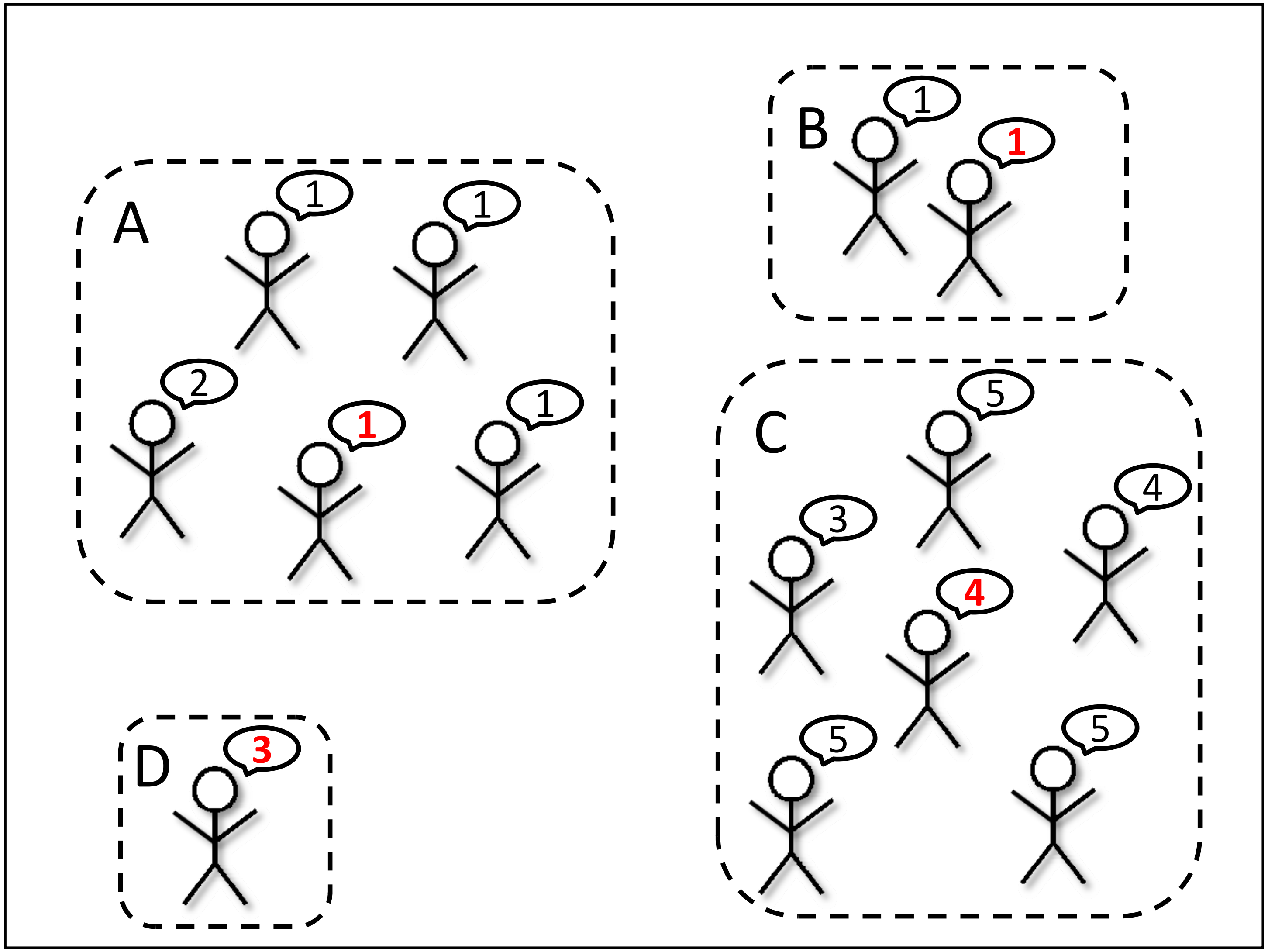
- Use average rating of other users within the same cluster to rate unseen items:

$$\hat{r}_u(i) = \frac{1}{|Cluster(u)|} \sum_{u' \in Cluster(u)} r_{u'}(i)$$

Cluster-Based Collaborative Filtering



Cluster-Based Collaborative Filtering



Rating using Nearest Neighbors

- Can also infer ratings based on nearest neighbors
- Similar to *K*-nearest neighbors clustering
- Weight ratings of nearest neighbor according to similarity

$$\hat{r}_u(i) = \overline{r}_u + \frac{1}{\sum_{u' \in \mathcal{N}(u)} sim(u,u')} \sum_{u' \in \mathcal{N}(u)} sim(u,u')(r_{u'}(i) - \overline{r}_{u'})$$

- Best to use (rating - average rating) because ratings are relative, not absolute

Evaluating Collaborative Filtering

- Standard metrics, such as precision are too strict for evaluating recommender systems
- Want to quantify how different predicted rating are from actual ratings
  - Absolute error

$$ABS = \frac{1}{|\mathcal{U}||\mathcal{I}|} \sum_{u \in \mathcal{U}} \sum_{i \in \mathcal{I}} |\hat{r}_u(i) - r_u(i)|$$

  - Mean squared error

$$MSE = \frac{1}{|\mathcal{U}||\mathcal{I}|} \sum_{u \in \mathcal{U}} \sum_{i \in \mathcal{I}} (\hat{r}_u(i) - r_u(i))^2$$

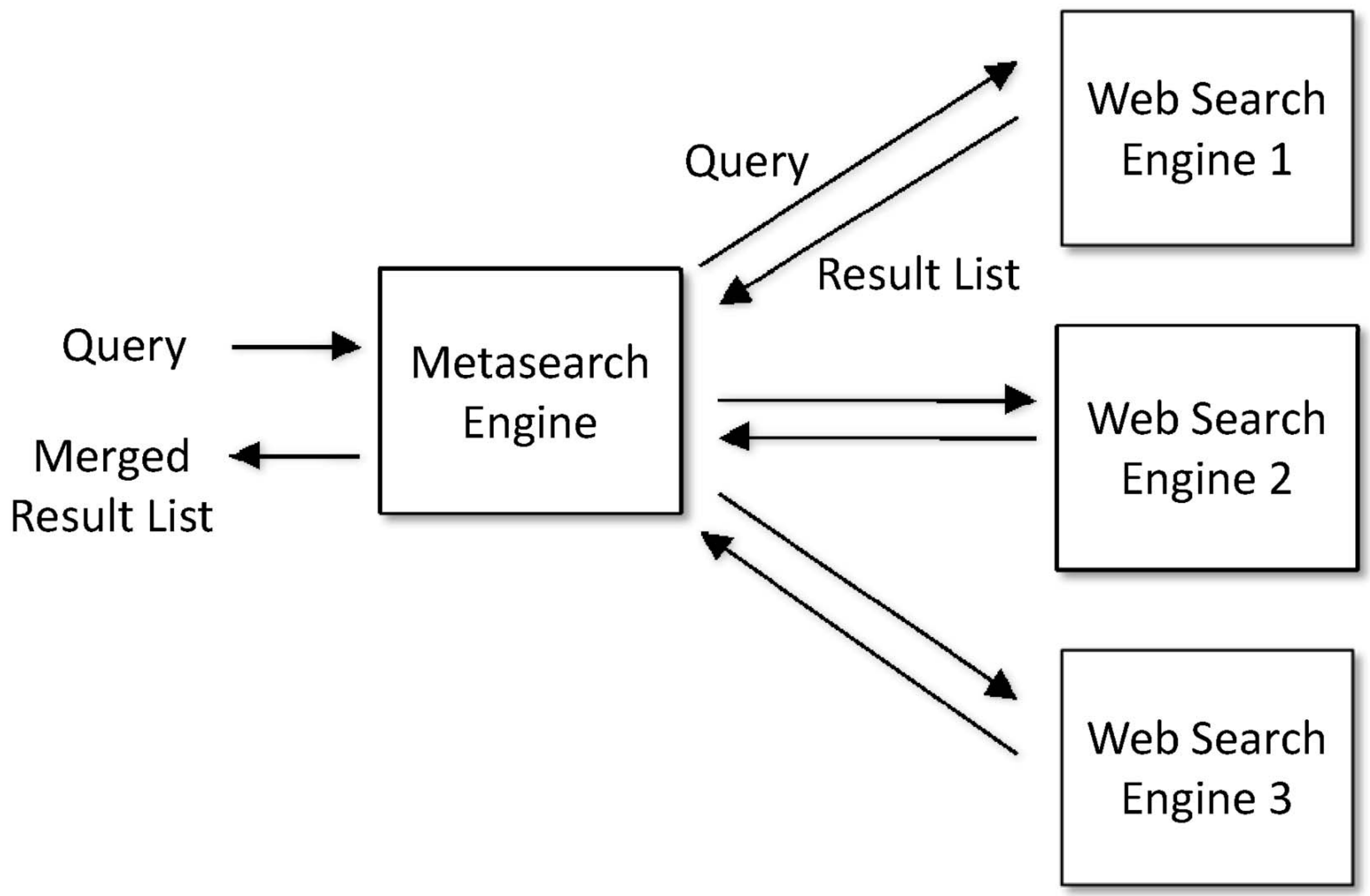
Distributed Search

- What is distributed search?
  - Searching over networks or communities of nodes
  - Each node contains some searchable data
- Distributed search applications
  - Metasearch
    - Node: search engines
    - Data: index
  - Peer-to-peer (P2P)
    - Node: user machines
    - Data: index, files, etc.

Distributed Search Tasks

- Resource representation
  - How is a node represented?
- Resource selection
  - Which nodes should be searched for the given information need?
- Result merging
  - How do we combine the results obtained from all of the nodes?

Metasearch Engine Architecture



Resource Representation and Selection Using Language Models

- Resource representation
  - Language model of the documents on the node
  - If document statistics are not available, a model can be estimated using query-based sampling
- Resource selection
  - Given a query, rank resources according to the likelihood their language model generated the query

Result Merging

- Scores returned from each resource may not be comparable
- Must normalize the scores to produce a ranked list for the merged results
- Scores can be normalized using:

$$S'_d = S_d(\alpha + (1 - \alpha)R'_d)$$

$$R'_d = (R_d - R_{min})/(R_{max} - R_{min})$$

- S_d is the local score, R_d is the resource score, and R_{min} and R_{max} are the minimum and maximum scores returned from the resource

Result Merging for Metasearch

- Merging results in metasearch is different because the same result may appear in multiple result sets
- Scores from various search engines can be combined as follows:

$$S'_d = n_d^\gamma \sum_{i=1}^{k} S_{d,i}$$

- N_d is the number of result sets that contain *d* and γ is typically set to -1, 0, or 1
- γ = 1 (often called CombMNZ) has been shown to be highly effective for combining scores

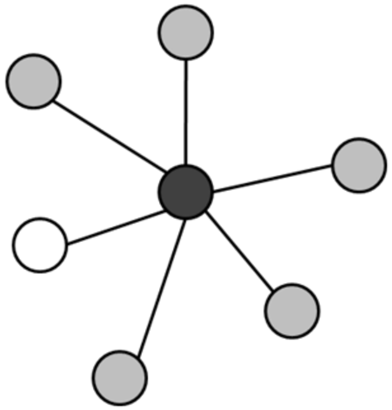
Peer-to-Peer Networks

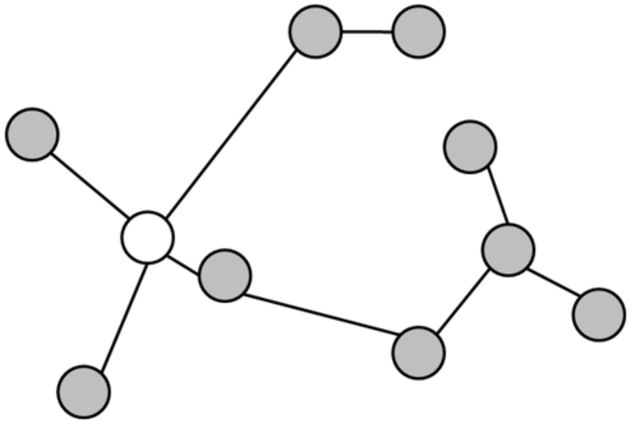
- Communities of users sharing data and files
  - KaZaA
  - BearShare
  - BitTorrent
- *Clients* issue queries to initiate search
- *Servers* respond to queries with files and may also route queries to other nodes
- Nodes can act as clients, servers, or both, depending on the network architecture

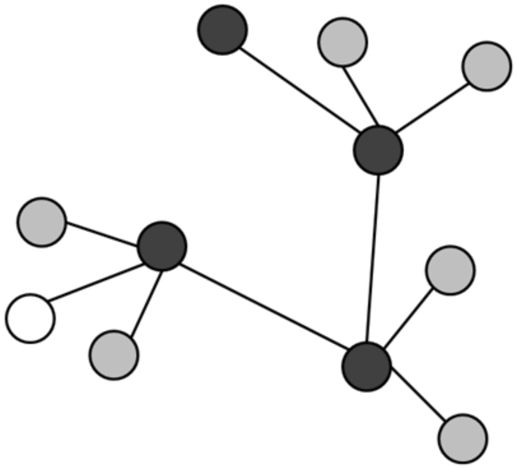
P2P Architectures

- Central hub
  - Clients send queries to hub, which routes them to nodes that contain matching files
  - Susceptible to attacks on the central hub
- Pure P2P (Gnutella 0.4)
  - Queries *flooded* into network with limited *horizon*
  - Connections between nodes are random
  - Nodes only know about neighbor nodes
  - Does not scale well
- Hierarchical (Superpeer Network)
  - Two-level hierarchy of hub nodes and leaf nodes
  - Leaf nodes are either clients or servers and only connect to hubs
  - Hubs provide directory services for the leaf nodes

Distributed Search Architectures


Central Hub


Pure P2P


Hierarchical P2P

Network Neighborhoods

- Flooding is inefficient due to the network traffic generated
- Rather than generating descriptions for each node, generate them for *neighborhoods* of nodes
- Improve efficiency of query routing

Neighborhoods of a Hub Node